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Abstract: Preference for water quality and its nonmarket valuation can be used to inform the development of pricing policies and long term supply strategies. Tap water quality is a household concern. The objective status quo varies between households and not between individuals within households, while charges are levied on households not individuals. Individual preferences differ from collective preferences. In households where there are two adults, we examine the preferences of each separately and then as a couple in collective decisions. We show the level of influence each has in developing the collective decision process. We use discrete choice experiments to model preference heterogeneity across three experiments on women, men and on both. We propose a random utility model which decomposes the error structure in the utility of alternatives so as to identify the individual influence in collective decisions. This approach to choice data analysis is new to environmental economics.

**The influence of individuals in forming collective**

**household preferences for water quality**

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Running title of less than 50 characters (Estimating household preferences for water quality)

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# The influence of individuals in forming collective household preferences for water quality

## Abstract

Preference for water quality and its nonmarket valuation can be used to inform the development of pricing policies and long term supply strategies. Tap water quality is a household concern. The objective status quo varies between households and not between individuals within households, while charges are levied on households not individuals. Individual preferences differ from collective preferences. In households where there are two adults, we examine the preferences of each separately and then as a couple in collective decisions. We show the level of influence each has in developing the collective decision process. We use discrete choice experiments to model preference heterogeneity across three experiments on women, men and on both. We propose a random utility model which decomposes the error structure in the utility of alternatives so as to identify the individual influence in collective decisions. This approach to choice data analysis is new to environmental economics.

**Keywords:** structural choice model, household preference, tap water, preference heterogeneity

## 1. Introduction

Tap water is a typical complex good that is provided at the household level and which can be decomposed into a number of attributes. While tap water is certainly a good familiar to all members of households, each member may display substantially different tastes for its attributes. Because of the composite nature of welfare changes in household water supply, due to this intra-household heterogeneity of taste, conducting stated surveys based on a representative of the household might

25 lead to misleading results. This is an important issue from the empirical viewpoint and motivates  
26 our study.

27         The theoretical and applied literature on household economics has made substantial progress  
28 in modelling joint preferences in marketing and transport (Arora and Allenby, 1999; Adamowicz et  
29 al., 2005; Hensher et al., 2008; Marcucci et al., 2010), whereas with few exceptions (Dosman and  
30 Adamowicz 2006, Bateman and Munro 2005, Strand 2007, Beharry-Borg et al. 2009) less progress  
31 has been made in terms of empirical applications in the field of non-market valuation. Investigating  
32 preferences from choice data coming from group decisions, rather than individual decisions,  
33 requires the ability to handle latent correlations amongst individual and joint choices in a structured  
34 manner. In the context of tap water, results obtained from disentangling individual preferences in  
35 group decisions have important implications for both policy and survey practice. These implications  
36 are of particular salience when preference surveys are designed to inform the process of definition  
37 or/and negotiation of water tariff between water utilities and regulatory bodies in charge of  
38 evaluating the adequacy of the tariffs and the economic management of investment by water  
39 utilities. At the time of data collection for this study this was of particular relevance in Italy, where  
40 recent legislation was intended to shift the control of water supply to newly constituted local water  
41 network utilities, with the intent of directing water management to be more responsive to market  
42 forces. The debate over this legislation proposal has been relegated to backstage after the results of  
43 a national referendum (12-13 June 2011 on the composition of water tariffs), but the focus on cost  
44 efficiency and social benefits is still driving the debate.

45         In this study we use data from a widely employed form of stated preference survey for  
46 multi-attribute goods, choice experiments (Adamowicz et al., 1998). The salient feature of the data  
47 collection is that members of households have provided choice responses first as individuals, and  
48 then jointly as a family. To adequately investigate preference heterogeneity of household members  
49 for tap water one of the main issues is how to empirically measure these differences, considering  
50 that results can be quite sensitive to choice of model specification. Previous work usefully

51 employed power function approaches based on the concept that the household's indirect utility is  
52 determined by a convex combination (a power function) of the indirect utility of man and woman  
53 (Dosman and Adamowicz 2006). This was later extended to power functions at the single attribute  
54 level. That is, the contribution of each attribute to the household's utility function was modelled as a  
55 convex combination (Beharry, Hensher and Scarpa 2009), with the power parameter specified as a  
56 household specific random component.

57         Within this context, we now explore the use of an innovative modelling approach, that we  
58 call structural choice modelling (hereafter SCM). SCM is an alternative econometric framework for  
59 modelling choice data using latent variables, by combining data generated from separate but related  
60 surveys and thereby simultaneously modelling choice outcomes from several DCEs (Rungie, 2011;  
61 Rungie et al., 2010, 2011; Coote et al., 2011). With respect to previous applications in  
62 environmental economics this approach allows two advantages: (i) the incorporation of latencies  
63 and (ii) the simultaneous estimation of structural causal factors from individual and joint choice.

64         SCM is designed to incorporate latent variables and structural equations into the analyses of  
65 DCEs and, more generally, into choice processes (McFadden, 1974; 2001). There are indeed several  
66 important precursors to SCM. Firstly, factor analytic models have been used to study brands in a  
67 product category. This is as if "brand" is an attribute and the individual brands are levels. Factors  
68 have been applied across brands and other attributes by Elrod (1988), Elrod and Keane (1995),  
69 Keane (1997) and Walker (2001). Secondly, factor analytic models have also been applied to the  
70 characteristics of respondents by using indicator variables (Walker, 2001; Ashok et al., 2002;  
71 Morikawa et al., 2002; Temme et al., 2008; Bolduc and Daziano, 2010; Yáñez et al., 2010; Hess  
72 and Stathopoulos, 2011). Thirdly, methods using latent variables have been developed for the  
73 analysis of combined RP and SP data (Ben-Akiva and Morikawa, 1990; Hensher et al., 1999;  
74 Louvier et al., 1999; Ben-Akiva et al., 2002; Louviere et al., 2002; Morikawa et al., 2002). The  
75 various approaches differ in the nature of the covariates employed; in the first the covariates are the

76 attributes of the alternatives and in the second the characteristics of the respondents. However, all  
77 approaches rely on similar mathematics.

78 SCM adapts this mathematics to extend the analysis of the attributes. In particular, it adds to  
79 the factor analytics the capacity to specify simultaneous equations and correlations (Jöreskog, 1970,  
80 1973; Bollen, 1989; Jöreskog and Sörbom, 1996) and it exploits the potential relationships between  
81 uses and choice outcomes (Rungie, 2011; Rungie et al., 2011; Coote et al., 2011).

82 In the traditional random coefficient model (e.g. Ben-Akiwa et al., 1997; McFadden and  
83 Train, 2000; Dube et al., 2002; Train, 2009), the coefficients for each covariate are independent  
84 random variables with means and variances estimated from the data; i.e. the variance covariance  
85 matrix, denoted by  $\Sigma$ , is either diagonal or with off-diagonal elements that refer to only covariances  
86 between random coefficients. In SCM the coefficients have a multivariate distribution where,  
87 through the parsimonious use of factor analytics in the form of simultaneous equations and  
88 correlations,  $\Sigma$  can be significantly more complex, yet structured. Although to be practical, the  
89 number of parameters must not be excessive. In addition competing models, i.e. competing  
90 specifications for the structure of  $\Sigma$ , can be empirically evaluated. In other words, the factor  
91 analytics are used to bring testable correlation structures to the error component nature of mixed  
92 logit models. The contribution of SCM is in its capacity to specify and evaluate competing models  
93 for how preferences for attributes are related. Error component models, of the type explored to  
94 define flexible substitution patterns between alternatives (Brownstone and Train 1999, Herriges and  
95 Phaneuf 2002, Thiene and Scarpa 2008) can also be seen as special cases of SCM specifications.

96 The present study adds to the existing literature in several ways. First, it is one of the few  
97 existing applications of structural choice models to investigate latency in preference heterogeneity.  
98 Second, to our knowledge this is the first empirical study using this approach in the field of  
99 environmental and resource economics. Ultimately, it is one of the few contributions using data

100 from more than two choice experiments that are simultaneously modelled within a natural group,  
101 such as the couple.

102 The rest of the paper is organized as follows. The next section illustrates the methodology.  
103 Survey and data are described in section 3, whereas section 4 defines model specifications and  
104 provides a discussion of result estimates. The last section concludes.

105

## 106 **2. Methods**

107 In this section we start by laying out a notation that we then use to move from the conventional and  
108 by now quite familiar mixed logit model to what we call a structural (equation) choice model or  
109 SCM. In the latter latent variables are brought to bear so as to develop a plausible structure of  
110 correlation across the determinants of choices. In our application we focus on a plausible structure  
111 between choice by members of the same residential unit (man and woman) and their joint  
112 deliberations. Specifically, we try to account for influences of individual taste coefficients of single  
113 respondents in a household as latent determinants of choice in the joint household decisions.  
114 Following Rungie et al. (2011) it is conceptually desirable to cast the approach around the familiar  
115 random utility framework.

116 Traditional random utility theory (McFadden, 1974; 2001; Train, 2009) states that  
117 alternative  $i$  is perceived to deliver utility  $u_i$ . This is composed of a systematic component  $v_i$ , and an  
118 error term,  $\varepsilon_i$ , which may be GEV or Gumbel distributed<sup>1</sup>.

$$119 \quad u_i = v_i + \varepsilon_i \quad (1)$$

120 The systematic components,  $v$ , are specified to be linear combinations of the  $m$  covariates in the  
121 vector  $x$  with random coefficients grouped in the vector  $\beta$ . To illustrate the structural choice model  
122 proposed here Rungie et al. (2011) used a notation and approach that is borrowed from the

---

<sup>1</sup> For simplicity the subscripts for the individual, the choice set and alternative within the choice set are omitted.



conventions employed in the broad literature of structural equation modelling and adapted to choice modelling. However, this would not be a familiar notation for those who, such as this audience, have been exposed to the conventional mixed logit notation. So, in order to facilitate the understanding of the proposed notation we proceed as follows. We note that in random parameter logit with a continuous mixture of taste the individual taste coefficient for a given attribute  $x_k$  is composed of two additive terms: the mean value of the taste parameter for the  $k^{\text{th}}$  covariate  $\beta_k$  and its random idiosyncratic component  $\sigma_k \tilde{\beta}_{kn}$ , where  $\tilde{\beta}_{kn}$  is the random component drawn by some distribution (perhaps standard normal) for the  $n^{\text{th}}$  individual and  $\sigma_k$  is the dispersion parameter for this random element to be estimated. So, omitting the subscript  $i$  for the single choice selection and  $n$  for the respondent, the conventional mixed logit notation for the systematic component of the utility is given by

$$v = \sum_k (\beta_k + \sigma_k \tilde{\beta}_k) x_k. \quad (2)$$

Rather than being a single random entity, in the SCM  $\tilde{\beta}_k$  can be expressed as a structural equation:

$$\tilde{\beta}_k = a_{k,1} \tilde{\beta}_1 + \dots + a_{k,m} \tilde{\beta}_m + \delta_k \quad (3)$$

where the  $a_{..}$  are elements from a matrix of regression parameters and the  $\delta_k$  are elements from a vector of random components, from which after estimation measures of fit, such as the classic R-squares, can be derived. These help to evaluate the overall model and the suitability of the proposed constructs.

From the above equations, it can be seen that the variance-covariance matrix of  $\tilde{\beta}$  is considerably more structured than a simple diagonal matrix. In other words, specific correlation structures can be imposed on the coefficients for the covariates. In a way, structural choice modeling (SCM) can be seen as an extension of error component modeling of the mixed logit model

146 as described in Brownstone and Train (1999), Train (2009) and Herriges and Phaneuf (2002) in the  
147 context of flexible substitution patterns.

148 Typically, the random components  $\delta$  in equation (3) are specified to have Gaussian  
149 distributions, but other distributions can also be assumed. In estimation via simulated maximum  
150 likelihood the expectation of mixtures of choice probabilities is obtained via variance reduction  
151 techniques based on quasi-random draws. In this application we use Halton draws for their well-  
152 known equidispersion properties (Train 1999), but others can be used (Baiocchi 2005).

153 From the above it should be apparent that two special cases of the utility structure  
154 underlying observed choice that we presented so far—the traditional fixed and random coefficient  
155 models—need not be addressed by means of SCM. Indeed standard software packages can be used  
156 and results from identical models on the same data will differ slightly due to differences in  
157 maximization algorithms and features of simulation techniques. In what follows we use SCM to  
158 create an ‘Influence Model’, which is designed to uncover the latent structure of correlated choices  
159 in couples. Specifically, we focus on the influences between men and women individual preferences  
160 and their joint choices as couples. In the process we highlight some stylized identification issues  
161 that are typical of SCM. We do so by presenting utility specifications in both the preference and  
162 WTP-space for panel data, which are the most frequently utility specifications used in non-market  
163 valuation studies from DCEs. For a discussion of the advantages and disadvantages of the two  
164 approaches in non-market valuation the interested reader is directed to Train and Weeks (2005),  
165 Scarpa, Thiene and Train (2008), and to Daly, Hess and Train (2012).

166

### 167 **3. Survey and Data**

168 The study is based on survey data collected with face-to-face DCEs interviews of 80 couples. One  
169 group of 20 couples was sampled in the city of Torino in the North-West. A second group of 60  
170 couples was obtained in the city of Vicenza, in the North-East. The two locations in terms of water  
171 quality are similar for a variety of reasons not discussed here, but mainly linked to their proximity

172 to the Alps. The motivation for investigating preferences for residential tap-water is to be found in  
173 the recently debated reforms of the national legislation regulating water utilities, which considered  
174 shifting the control of water supply to newly constituted authorities with the intention to make water  
175 supply more market driven. This would turn out to be challenging for municipalities, because it will  
176 force them to implement a series of changes in water utility management by merging water  
177 management utilities across local authorities and creating new locally regulated commercial entities.  
178 Therefore, local water authorities (Integrated Water Services) are interested in investigating  
179 preference heterogeneity for tap water quality attributes to strategically define water tariffs across  
180 city locations.

181

### 182 **3.1 Data**

183 The data used here come from an explorative and preliminary survey specifically designed to  
184 prepare a more complex data collection, which will be the subject of another application. The  
185 application provided here is for the purpose of proof of concept. As mentioned above, reported  
186 results are based on interviews of 80 couples, which in total provided 1,920 choice responses from 8  
187 choice tasks with four alternatives each. Choices were expressed by 160 respondents individually  
188 (80 men and 80 women) which then also provided 80 sets of joint decisions.

189 In the survey, respondents were asked to choose among alternatives described using the same  
190 attribute structure, which differed on the basis of four quality attributes relating to drinking water  
191 characteristics plus the cost (Chlorine Odour, Chlorine Taste, Water Turbidity, Calcium Carbonate  
192 Stains and Cost). Cost was described as an additional amount of money people would pay in the  
193 water bill over a year. In particular, respondents were asked to choose among water service supply  
194 contracts displaying different levels of water supply characteristics or “water service factors” to use  
195 a term commonly employed in similar utility studies (Willis and Scarpa 2005) and in the UK water  
196 industry. The attributes and the relative levels are reported in table 1. Respondents were asked to  
197 choose between the frequencies of events in which they could smell (odour) and/or taste chlorine

198 (once a day, once a week, once a month, never or always). Turbidity due to fine air bubbles was  
199 also considered. Its levels included its absence, and its presence in a mild, medium and extreme  
200 form. Due to the hardness of water in this area calcium carbonate staining in pipes is quite a  
201 concern and the effect of presence/absence of staining was also investigated. In the survey  
202 respondents faced four alternatives in each choice set, where one alternative was always the status  
203 quo and involved no additional cost. An example of choice set is reported in table 2.

204 The design of the survey was finalized by contacting and interviewing experts employed by  
205 local utilities supplying Integrated Water Services (water supply as well as water treatment  
206 services). These provided specific and technical information which turned out to be valuable in the  
207 selection of the attributes levels. This information was supplemented with suggestions provided by  
208 technicians from public institutions involved in the management of such water services. The  
209 combined information was then used to conduct repeated focus groups, the results from which were  
210 then used to design the choice experiments. The complete questionnaire was then tested in the field  
211 in a pilot survey, which also provided priors for the coefficient values to be used in the Bayesian  
212 design.

213 The choice data from each household were collected first with man and woman conducting  
214 individual experiments and being asked their individual preferences. Then, it proceeded by asking  
215 man and woman to join together in a choice exercise to select favourite alternatives for the  
216 household. In this way for each household we collected 3 sets of choices, one for the man, one for  
217 the woman and one for the household.

218

### 219 ***3.2 Experimental design***

220 The survey employed a sequentially adapted experimental design and one of the aims of the  
221 research was to use the information collected with the first design as a prior to inform the  
222 subsequent ones. In particular, in the survey was used a sequential efficient Bayesian design. The  
223 purpose was to ensure a high accuracy of the estimates despite the relatively small sample size

224 affordable. One of the main advantages of such an approach is that as more responses are collected  
225 during the course of the survey, gradually more accurate information becomes available on the  
226 priors of the population, thereby increasing the efficiency of the final estimates and decreasing the  
227 potential for mis-specification (Kanninen 2002; Scarpa et al. 2007; Ferrini and Scarpa 2007; Scarpa  
228 and Rose, 2008; Kerr and Sharp, 2010; Vermeulen et al., 2011).

229 In the Turin sample, the overall survey design was articulated in subsequent phases, as  
230 additional information was sequentially collected in six waves of sampling. Each sample wave used  
231 a different  $WTP_b$ -efficient design<sup>2</sup> developed using Bayesian priors (as indicated by the subscript  
232 “b”), derived by combining the information collected in all previous waves. The initial prior  
233 information was gathered from the pre-test and the pilot survey; the first wave of interviews then  
234 informed in turn the design of the following waves. At the end of waves 1-6 basic multinomial logit  
235 models were estimated so as to provide priors for the efficient design of the subsequent sample  
236 wave. Each respondent tackled 8 choice tasks.

237 For the second group of respondents in Vicenza we employed a Bayesian D-efficient design  
238 (Sandor and Wedel, 2001; Ferrini and Scarpa, 2007; Rose and Bliemer, 2009), derived on the basis  
239 of existing information on parameter estimates previously obtained from the previous study. The

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<sup>2</sup> Specifically, the  $WTP_b$ -efficient criterion was adopted to select the fraction of the full factorial to be used as a design in the sequence of sub-samples. This is based on the minimization of the expected variance of some non-linear functions of the utility coefficients, namely the sum of the variances of the marginal willingness to pay estimates. Considering that different attributes can be described in different units, as in the case at hand, Scarpa and Rose (2008) point out that the minimisation process of variance sum across marginal WTPs with uneven unit of measurement may result in an unsatisfactory outcome. To overcome such a limitation, they suggest the adoption of a criterion that maximizes the minimum  $t$ -value for the marginal WTP. This choice places more emphasis on the attribute whose WTP was estimated with least accuracy, as measured by the  $t$ -value. We note in passing that Bayesian WTP-efficiency has also been found to provide designs with higher robustness to outliers and less prone to producing extreme WTP estimates (Vermeulen et al., 2010).

240 point estimates from the earlier Turin study were used to inform the prior distribution on the  
241 Bayesian design for Vicenza, while the standard errors were used to define the variances of the  
242 distributions of priors. The probabilities in the derivation of the design were obtained via simulation  
243 using 200 Halton draws.

244

### 245 **3.3 Sampling**

246 The survey focussed on couples and the preferences of their two members. As a consequence it  
247 focussed on modelling joint choices as functions of primitive individual preferences of the two  
248 members of the couple (man and woman).

249 The survey developed in several stages. The first stage aimed at selecting households that could be  
250 considered as “couples” into a sampling frame. These were subjects living in a stable relationship  
251 with a partner. Then the sampling was randomly executed on this frame.

252 During the second stage, respondents were asked whether they would be willing to participate  
253 in the survey. They were contacted by mail first and then by telephone. Once both partners agreed  
254 on participation, the interviewer would fix an appointment to visit the couple. At the household’s  
255 house, they were debriefed jointly and given the stated preference tasks.

256 Importantly, in order to avoid that any difference in choice across individuals of the same  
257 household could be due to differences in choice tasks, each respondent within a given household  
258 unit was given the same sequence of choice tasks. These tasks were performed first individually, so  
259 as to derive individual preferences, and then jointly. When performed individually, respondents  
260 were asked their individual preferences. When performed jointly, they were asked to negotiate a  
261 mutually satisfying outcome for the couple.

262

## 263 4. Model specifications and estimates

264 In what follows we first illustrate the specifications of indirect utility for the preference space model  
265 because it is the most commonly employed. Later we will show the changes required for the WTP-  
266 space panel model.

267

### 268 4.1 Model specifications and rationale

269 The choice data is made of responses to three identical discrete choice experiments (DCEs)  
270 conducted separately. With  $y_w$  we denote the responses by women (DCE 1), with  $y_m$  those by men  
271 (DCE 2) and with  $y_j$  the joint responses provided as a couple (DCE 3). To simultaneously model  
272 choice probabilities for the separate DCEs the three data matrices were stacked at the household  
273 level. In each DCE the alternatives were described by using five attributes, three of which had 4  
274 levels defined as unimproved and 3 levels of improvement. In this study these were then aggregated  
275 into a dummy-coded variables denoting extreme improvement (the level of a disturbance was  
276 reduced to “never”). The fourth attribute (*stain*) had two levels and was also coded as a single  
277 dummy variable denoting the “presence” of stains. The fifth attribute was the cost (tariff) which was  
278 coded numerically in Euros. Because of dummy coding with each attribute (except cost) and the  
279 alternative specific constant for the status-quo in total there were six identifiable coefficients for the  
280 indirect utility function.

281 To evaluate the identification power of the SCM influence model in explaining unobserved  
282 heterogeneity we compare it with two standard logit specifications. In total, three logit probability  
283 models have been specified and estimated for the three data sets: (i) the *fixed coefficient model*, (ii)  
284 the *random coefficient model*, and (iii) the *influence model*. First, the fixed coefficient logit model  
285 was estimated, from which a mean value estimate ( $\beta_k$ ) for each attribute coefficient is obtained.  
286 Next, the well-known restrictive assumptions of the fixed coefficient logit model were relaxed by  
287 estimating a random coefficient panel model; this, besides mean values ( $\beta_k$ ), provided estimates of  
288 the dispersion parameter ( $\sigma_k$ ) for the random coefficients of each covariate.

289 Ultimately and more importantly, we pose the following question: is there a structural link in  
 290 the heterogeneity within the joint DCE and the heterogeneity in the separate DCEs by men and  
 291 women? The influence model specifies these links, in that the utilities for the joint decisions are  
 292 also a function of the individual utilities for women and men. Each utility in the joint DCE model is  
 293 simultaneously specified to be a linear function of the equivalent utilities in the women and men  
 294 DCEs. By doing so we wish to investigate if and, in case, to what extent, the joint decision making  
 295 process of couples is influenced by individuals. Within this exploration, as we will show, we can  
 296 also answer the question of whether women or men are most affecting joint decisions.

297 In the equations and model specifications below the attributes are referred to as follow:  
 298 odour=OD, taste=TS, turbidity=TR, stain=ST, cost=CO and status quo=SQ.

299

#### 300 **4.2 The Random Coefficient Model**

301 In this model, the four water factor services—odour, taste, turbidity and stain—are assumed to have  
 302 random coefficients. The other two attributes—cost and status quo—are given fixed coefficients.

303 For women's individual choices the random coefficient model involves the following  
 304 indirect utilities:

$$\begin{aligned}
 305 \quad v^{OD,w} &= (\beta^{OD,w} + \sigma^{OD,w} \tilde{\beta}^{OD,w}) x^{OD,w} \\
 306 \quad v^{TS,w} &= (\beta^{TS,w} + \sigma^{TS,w} \tilde{\beta}^{TS,w}) x^{TS,w} \\
 307 \quad v^{TR,w} &= (\beta^{TR,w} + \sigma^{TR,w} \tilde{\beta}^{TR,w}) x^{TR,w} \\
 308 \quad v^{ST,w} &= (\beta^{ST,w} + \sigma^{ST,w} \tilde{\beta}^{ST,w}) x^{ST,w} \\
 309 \quad v^{CO,w} &= \beta^{CO,w} x^{CO,w} \\
 310 \quad v^{SQ,w} &= \beta^{SQ,w} x^{SQ,w}
 \end{aligned} \tag{4}$$

311 and, for alternative  $i$ ,

$$312 \quad \mu_i^w = v_i^{OD,w} + v_i^{TS,w} + v_i^{TR,w} + v_i^{ST,w} + v_i^{CO,w} + v_i^{SQ,w} + \varepsilon_i^w \tag{5}$$



313 For men's individual choices and the joint decisions the random coefficient model repeats  
 314 the same structure.

315

### 316 **4.3 The Influence Model**

317 While the random coefficient model introduces heterogeneity across the panel of choices it does not  
 318 uncover any latent structure of choice between members of the same household. In particular, no  
 319 relation exists between the primitive of the utility function of the individuals in their choices and  
 320 their joint choice. Behaviourally this is clearly counter-intuitive and contrary to empirical findings  
 321 reporting corroborating evidence in favour of such correlation (Dosman and Adamowicz 2006;  
 322 Beharry, Hensher and Scarpa, 2009; Scarpa, Thiene and Hensher 2012). To account for this we  
 323 propose an SCM that elaborates further on the random coefficient model by imposing structure in  
 324 the correlation of the  $\tilde{\beta}$  s, but only for the joint choices. As in the random coefficient model the  
 325 primitive of the utility for women individual choices are expressed as independent random  
 326 coefficients.

$$\begin{aligned}
 \tilde{\beta}^{OD,w} &= \delta^{OD,w} \\
 \tilde{\beta}^{TS,w} &= \delta^{TS,w} \\
 \tilde{\beta}^{TR,w} &= \delta^{TR,w} \\
 \tilde{\beta}^{ST,w} &= \delta^{ST,w}
 \end{aligned}
 \tag{6}$$

328 The four random components  $\delta$  in (6) have independent standard Gaussian distributions leading to a  
 329 model for the women's individual choices identical to the random coefficient model in (4). For  
 330 men's individual choices the influence model repeats the same structure.

331 Things are different for the joint decisions, which have random components specified as  
 332 linear combinations applied to the primitive utilities:

$$\begin{aligned}
333 \quad & \tilde{\beta}^{OD,j} = a^{OD,w} \tilde{\beta}^{OD,w} + a^{OD,m} \tilde{\beta}^{OD,m} + \delta^{OD,j} \\
334 \quad & \tilde{\beta}^{TS,j} = a^{TS,w} \tilde{\beta}^{TS,w} + a^{TS,m} \tilde{\beta}^{TS,m} + \delta^{TS,j} \\
335 \quad & \tilde{\beta}^{TR,j} = a^{TR,w} \tilde{\beta}^{TR,w} + a^{TR,m} \tilde{\beta}^{TR,m} + \delta^{TR,j} \\
336 \quad & \tilde{\beta}^{ST,j} = a^{ST,w} \tilde{\beta}^{ST,w} + a^{ST,m} \tilde{\beta}^{ST,m} + \delta^{ST,j}
\end{aligned} \tag{7}$$

337 where  $a$  denotes the regression coefficients. The four random components  $\delta$  in (7) have independent  
338 Gaussian distributions with means zero but with standard deviations to be estimated from the data  
339 (error components). Then, the indirect utilities are:

$$\begin{aligned}
340 \quad & v^{OD,j} = \left( \beta^{OD,j} + \sigma^{OD,j} a^{OD,w} \tilde{\beta}^{OD,w} + \sigma^{OD,j} a^{OD,m} \tilde{\beta}^{OD,m} + \sigma^{OD,j} \delta^{OD,j} \right) x^{OD,j} \\
341 \quad & v^{TS,j} = \left( \beta^{TS,j} + \sigma^{TS,j} a^{TS,w} \tilde{\beta}^{TS,w} + \sigma^{TS,j} a^{TS,m} \tilde{\beta}^{TS,m} + \sigma^{TS,j} \delta^{TS,j} \right) x^{TS,j} \\
342 \quad & v^{TR,j} = \left( \beta^{TR,j} + \sigma^{TR,j} a^{TR,w} \tilde{\beta}^{TR,w} + \sigma^{TR,j} a^{TR,m} \tilde{\beta}^{TR,m} + \sigma^{TR,j} \delta^{TR,j} \right) x^{TR,j} \\
343 \quad & v^{ST,j} = \left( \beta^{ST,j} + \sigma^{ST,j} a^{ST,w} \tilde{\beta}^{ST,w} + \sigma^{ST,j} a^{ST,m} \tilde{\beta}^{ST,m} + \sigma^{ST,j} \delta^{ST,j} \right) x^{ST,j} \\
344 \quad & v^{CO,j} = \beta^{CO,j} x^{CO,j} \\
345 \quad & v^{SQ,j} = \beta^{SQ,j} x^{SQ,j}
\end{aligned} \tag{8}$$

346 The heterogeneity of the women's individual choices is exogenous, specified by the  
347 independent  $\delta$  in (6). So too is the heterogeneity of the men's individual choices. However, in (7)  
348 the heterogeneity for the *joint* decisions is now a combination of an exogenous effect, specified as  
349 the  $\delta$ , and an endogenous effect, specified by including the  $\tilde{\beta}^{\cdot w}$  and  $\tilde{\beta}^{\cdot m}$  terms.

350 As discussed below, the influence model was fitted to the data in two similar forms, the full  
351 model (Full) and a slightly simplified model (S) without redundancies, which in the empirical  
352 analysis shows to fit the data just as well.

353

#### 354 **4.4 Preference space estimates**

355 All models have been estimated by using DiSCos (Rungie, 2011)<sup>3</sup>. The estimates of the mean  
356 values of the preference space model with fixed taste coefficients, reported in Table 3, show  
357 expected signs and high significance for all attributes. All coefficients for the “never” smell and  
358 taste for chlorine and the no turbidity display positive intensities of taste. Women show less  
359 inclination to adhere to the status-quo than men and what emerges from joint decisions.

360 Table 4 reports the statistics for the fit of the various preference space models. As it can be  
361 noted by comparing the log-likelihood values, the random coefficient model (see Table 5 for result  
362 estimates) performs better than the fixed model, as one would expect. Nevertheless the influence  
363 model gives the best fit. The improvement in terms of performance is substantial, with more than 70  
364 points, thereby supporting our hypothesis of existence of a latent structure in the unobserved  
365 heterogeneity. Information criteria that penalize for over parameterization, such as AIC, AIC3 and  
366 BIC, are concordant to indicate this model to provide best fit.

367

##### 368 4.4.1 Identification of the Influence Model

369 The SCM model might be challenging in its identification requirements. It is easy to establish if a  
370 SCM is identified: (i) If the Hessian matrix cannot be inverted then the model is not identified; (ii)  
371 If many of the more substantive parameters have *t*-values close to zero then most likely there is also  
372 a problem with identification. Confounding occurs when two parameters are not identified but their  
373 product is. The result is a ridge in the plot of the log likelihood function. The Hessian may not be  
374 invertible but if it is some of the standard errors will be quite large; (iii) If fixing individual  
375 parameters to zero, or some other theoretically justifiable value, does not reduce the optimum log  
376 likelihood and fit of the model, then the parameter need not be estimated from the data.

---

<sup>3</sup> Structural choice models were estimated by means of a software program called DiSCos (Rungie, 2011) and written in MatLab by using 10,000 Halton draws. Estimation of each model with relatively good starting values took about a week in a Dell M6500 quad core 64 bit computer.

377 Through practical experience guidelines are developing for creating properly identified  
378 SCMs. To reduce the risk of confounding, a usual practice, which is discussed further below, is to  
379 fix the standard deviations of the random components  $\delta$  to one.

380 The influence model as it is described above has 42 parameters. There are three DCEs,  
381 women, men and joint, each with six attributes creating a total of 18 mean estimates in  $\beta$ . In each  
382 DCE four attributes, OD, TS, TR and ST, have random coefficients with dispersion parameters  $\sigma$   
383 creating a total of 12. The same four attributes in the women and men experiments influence the  
384 preferences in the joint experiment creating a total of 8 regression parameters  $a$ . Finally, as in (7),  
385 the four  $\delta$  in the joint experiment each have a standard deviation to be estimated. Thus, there are in  
386 total 42 parameters to estimate from the data. Not all are identified.

387 In the joint DCE, for any one attribute, (7) indicates a confounding between three  
388 parameters; the regression coefficients  $a$ , the dispersion parameter  $\sigma$  and standard deviation of  $\delta$ .  
389 One of the three is not identified. As a comparison, in the women and men experiments the standard  
390 deviation of  $\delta$  is fixed to one leading to the remaining dispersion parameter,  $\sigma$ , being identified.  
391 Exploratory data analysis indicated that for the joint experiment a similar approach of fixing the  
392 standard deviation of  $\delta$  to one was not appropriate as it reduced the ability to interpret the  
393 regressions parameters  $a$ . As an alternative, the standard deviation of  $\delta$  were free to be estimated  
394 from the data, and some regression parameters,  $a$ , were fixed. This led to the (full) influence model  
395 having 38 identified parameters. The results are in Table 4.

396 Specifically, for the influence of the women on the joint DCE the regression parameters  
397 were all fixed to one; i.e.  $a^{OD,w} = a^{TS,w} = a^{TR,w} = a^{ST,w} = 1$ . This is as if the influence of the women  
398 were standardized. The influence of the men on the joint experiment is then evaluated by comparing  
399 the equivalent regression parameters,  $a^{OD,m}$ ,  $a^{TS,m}$ ,  $a^{TR,m}$  and  $a^{ST,m}$ , to the standard of one. But the  
400 model does not assume there is influence, not does it impose it. In the joint DCE the combined roles  
401 of the dispersion parameter,  $\sigma$ , and the standard deviation of the random component  $\delta$  determine the  
402 relative exogenous and endogenous effects on heterogeneity. The degree of influence is determined

by the data. The results are discussed below but first we examine the goodness-of-fit for the four regressions in (7) by focussing on their R-squares.

#### 4.4.2 Simplifying the influence model

The R-squares for the four regressions equations in the Influence Model (Full) are reported in Table 6. The estimates of the standard deviations for the four  $\delta$  in (7) were all so close to zero that the R-squares are all 100%. The result does not indicate that the decision making in the joint experiment was deterministic when conditioned on the women and men experiments. Rather, the result indicates that all the heterogeneity in the joint experiment can be accounted for by heterogeneity from the separate women and men experiments and that the expressions  $\delta^{OD,j}$ ,  $\delta^{TS,j}$ ,  $\delta^{TR,j}$  and  $\delta^{ST,j}$  in (7) do not contribute to the fit of the model. This is a strong result, but it is unsurprising. The DCEs for women and men were conducted first. Then the joint DCE was conducted immediately after. Apart from the heterogeneity influencing the women and men DCEs, there was no opportunity for a new exogenous source of heterogeneity to influence the joint DCE.

Consequently, the model in (7) was simplified as in (9); the regression parameters,  $a$ , for women were fixed to one and standard deviations for the  $\delta$  in the joint experiment were fixed to zero, giving rise to the following latent structure:

$$\begin{aligned}\tilde{\beta}^{OD,j} &= \tilde{\beta}^{OD,w} + a^{OD,m} \tilde{\beta}^{OD,m} \\ \tilde{\beta}^{TS,j} &= \tilde{\beta}^{TS,w} + a^{TS,m} \tilde{\beta}^{TS,m} \\ \tilde{\beta}^{TR,j} &= \tilde{\beta}^{TR,w} + a^{TR,m} \tilde{\beta}^{TR,m} \\ \tilde{\beta}^{ST,j} &= \tilde{\beta}^{ST,w} + a^{ST,m} \tilde{\beta}^{ST,m}\end{aligned}\tag{9}$$

Table 4 shows this simpler form of the influence model (denoted by (S) from “simplified”) fitted the data just as well, confirming the redundancy of parameters in the full influence model. This reduced form is the model we use to evaluate the influence. Further results for the influence model (S), as are given in Tables 7 and 8, and are discussed below.

428

#### 429 4.4.3 Evaluating Influence

430 The estimates of the regression coefficients,  $a$ , are shown in Table 7. The influence of men on the  
431 attribute of odour in joint choices was greater than the influence of women. Conversely, the  
432 influence of women in joint choices was greater on the other three qualitative attributes, taste,  
433 turbidity and stain.

434 Aggregating over (the square of) the regression parameters for the four attributes identifies  
435 that women provided 58% of the heterogeneity in the joint experiment and men 42%. This  
436 conclusion, that women have greater influence, is further demonstrated by applying two constraints  
437 to the influence model (S). First, only women are specified as influencing the heterogeneity in the  
438 joint experiment, and second, only men. The results in Table 9 for these two models again show  
439 clearly that women have greater influence on the heterogeneity in the joint DCE than men.

440

#### 441 *4.5 Willingness-to-pay space for the influence model*

442 In willingness-to-pay space a strictly positive random component,  $\lambda$ , is applied multiplicatively to  
443 the systematic component of utility (Train and Weeks 2005). Since  $\lambda$  operationalises heterogeneity  
444 for scale and for the cost coefficient simultaneously, the cost coefficient in the indirect utility in the  
445 influence model in WTP space is set to -1.

446 Thus for women's individual choices the model from (4) has  $\beta^{CO,w} = -1$  and is:

$$\begin{aligned}
447 \quad v^{OD,w} &= \lambda^w (\beta^{OD,w} + \sigma^{OD,w} \tilde{\beta}^{OD,w}) x^{OD,w} \\
448 \quad v^{TS,w} &= \lambda^w (\beta^{TS,w} + \sigma^{TS,w} \tilde{\beta}^{TS,w}) x^{TS,w} \\
449 \quad v^{TR,w} &= \lambda^w (\beta^{TR,w} + \sigma^{TR,w} \tilde{\beta}^{TR,w}) x^{TR,w} \\
450 \quad v^{ST,w} &= \lambda^w (\beta^{ST,w} + \sigma^{ST,w} \tilde{\beta}^{ST,w}) x^{ST,w} \\
451 \quad v^{CO,w} &= \lambda^w (-1) x^{CO,w} \\
452 \quad v^{SQ,w} &= \lambda^w \beta^{SQ,w} x^{SQ,w}
\end{aligned} \tag{10}$$

453 For men's individual choices and the joint decisions the random coefficient model in WTP  
454 space repeats the same structure.

455 Similarly for the joint decisions (8) becomes:

$$\begin{aligned}
456 \quad v^{OD,j} &= \lambda^j (\beta^{OD,j} + \sigma^{OD,j} a^{OD,w} \tilde{\beta}^{OD,w} + \sigma^{OD,j} a^{OD,m} \tilde{\beta}^{OD,m} + \sigma^{OD,j} \delta^{OD,j}) x^{OD,j} \\
457 \quad v^{TS,j} &= \lambda^j (\beta^{TS,j} + \sigma^{TS,j} a^{TS,w} \tilde{\beta}^{TS,w} + \sigma^{TS,j} a^{TS,m} \tilde{\beta}^{TS,m} + \sigma^{TS,j} \delta^{TS,j}) x^{TS,j} \\
458 \quad v^{TR,j} &= \lambda^j (\beta^{TR,j} + \sigma^{TR,j} a^{TR,w} \tilde{\beta}^{TR,w} + \sigma^{TR,j} a^{TR,m} \tilde{\beta}^{TR,m} + \sigma^{TR,j} \delta^{TR,j}) x^{TR,j} \\
459 \quad v^{ST,j} &= \lambda^j (\beta^{ST,j} + \sigma^{ST,j} a^{ST,w} \tilde{\beta}^{ST,w} + \sigma^{ST,j} a^{ST,m} \tilde{\beta}^{ST,m} + \sigma^{ST,j} \delta^{ST,j}) x^{ST,j} \\
460 \quad v^{CO,j} &= \lambda^j (-1) x^{CO,j} \\
461 \quad v^{SQ,j} &= \lambda^j \beta^{SQ,j} x^{SQ,j}
\end{aligned} \tag{11}$$

463 The random coefficient  $\lambda$  has a lognormal distribution giving rise to two additional  
464 parameters, the mean  $\mu_\lambda$  and standard deviation  $\sigma_\lambda$  of the normally distributed  $\ln(\lambda)$ . The joint scale,  
465  $\lambda^j$ , is a function of the scales for woman,  $\lambda^w$ , and man,  $\lambda^m$ , and an error term  $\lambda^\delta$  where:  
466 in the linear form

$$467 \quad \ln(\lambda^j) = a^{\lambda,w} \ln(\lambda^w) + a^{\lambda,m} \ln(\lambda^m) + \ln(\lambda^\delta) \tag{12}$$

468 and in the multiplicative form

$$(\lambda^j) = (\lambda^w)^{a^{\lambda,w}} (\lambda^m)^{a^{\lambda,m}} (\lambda^o) \quad (13)$$

With eight new parameters to be estimated ( $\mu_\lambda$  mean and  $\sigma_\lambda$  for each of three  $\lambda$  and two  $a^\lambda$ ) and three former parameters fixed to -1 (the price coefficients, for women, men and joint) the influence model in willingness-to-pay space increases the number of parameters by 5 to a new total of 39. Comparing information criteria reported in Table 10 to Table 4 shows the WTP space model fits the data better than the preference space models, even accounting for parameter proliferation.

The estimates for the  $a$  parameters are in Tables 11. The estimates for the distribution parameters of  $\ln(\lambda)$  are in Table 12, where the total joint mean and dispersion is calculated using (12). The earlier preference space results in Table 3 report partworths for cost of -0.06 for woman and man and -0.04 for joint. The plot of the three log normal distributions for  $\lambda$  in WTP space in Figure 1 show results of a similar order and again the joint is lower. The upper tails represents the cases where there is a higher willingness to pay. There are more individuals in the upper tail for man and less for joint. An interpretation is that in the joint decisions extreme WTP positions mostly held by men are moderated down by women.

The estimates of the remaining parameters, in Table 13, can be compared with Table 8. The estimated means for cost in preference space in Table 8 are -.05 for woman, -.07 for man and -.04 for joint. By comparison, for WTP space in Table 8, the same parameters are all fixed to -1. Consequently, all other estimates in Table 8 are necessarily 20 times higher. Once this multiplicative scaling effect of  $\lambda$  has been accounted for the estimates for WTP space for each attribute are still higher, about double, but the order of importance of the attributes is unchanged.

98% of the variability in the joint  $\ln(\lambda)$  is accounted for by the variability in the crude  $\ln(\lambda)$  for woman and man. Thus the result for preference space that joint decisions can be accounted for by the individual woman and man decisions is confirmed in the WTP space for the heterogeneity in



494 the random behaviour of  $\lambda$ . In the joint decisions there is no other or new source of heterogeneity  
495 apart from the primitive man and woman decisions. Table 11 shows that again man has more  
496 influence on Odour but overall, as measured now through  $\ln(\lambda)$ , woman, at 66%, has much more  
497 influence than man at 32%.

498 The pooled willingness to pay for each attribute is the product of  $\lambda$  and the various forms of  
499  $\beta$  as in (9) to (12). The median results, reported in Table 14, show that removing Stain has the  
500 highest value and improvement in Taste the least. For Taste, Turbidity and Stain the joint decision  
501 is an averaging of the primitive decisions but not so for Odour where the dynamics of the joint  
502 decision raises the WTP. The first quartiles for Stain show the results for those willing to pay more.  
503 In every case for these quartiles the man has higher willingness to pay which is moderated in the  
504 joint decision by women. Conversely the first quartiles, and third for Stain, show the results for  
505 those with willingness to pay less. The joint decision raises this small willingness to pay for  
506 Turbidity and Stain. Finally, the correlations of women with joint and men with joint in Table 15  
507 show the same pattern as seen before. Women have much more influence in the joint decisions than  
508 men, especially, as shown in the quartile behaviours, in the case of men with extreme (low or high)  
509 WTPs.

510

## 511 **5. Conclusions**

512 The study of preferences underlying group decisions can be conducted by adequately developed  
513 surveys and the data of which are consistently analyzed by employing specifically developed choice  
514 models. While previous work has mostly employed power function approaches at the individual  
515 indirect utility level (Dosman and Adamowicz 2006) or at the single attribute level (Beharry,  
516 Hensher and Scarpa 2009), we offer an “influence model” based on a special structure of the  
517 idiosyncratic components of the joint choice. This is a special case of a broader approach to choice  
518 modeling developed by Rungie et al. (2011) and Coote et al. (2011) called structural choice  
519 modeling. As a proof of concept, we explore this approach in a small sample but high quality set of

520 discrete choice experiments conducted in households and investigating preferences for tap water.  
521 Tap water is a multi-attribute good that is appreciated differently by each member of a household.  
522 Yet, one single contract provides this utility at the household level. Household preferences should  
523 hence be based on joint decisions by members of the household. In an identical choice experiment  
524 conducted first individually and separately by husband and wife, and then jointly, we find that a  
525 structural model of choice greatly improves model fit.

526         We stop short of deriving estimates of welfare measures for specific policies because we  
527 favor the uncovering of structure in the heterogeneity of joint decisions. Overall we find the  
528 preliminary results worth of attention and the modeling approach informative. Further research  
529 should focus on other plausible specifications of influence across individual and joint choice as well  
530 as on deriving welfare estimates for specific policy proposals. Future work should also explore the  
531 predictive power of the model for joint group decisions in observations held out of sample during  
532 estimation, but based on the individual preferences of the group.

533

534

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668 Table 1. Description of the qualitative attributes  
 669

| Variable name | Attribute |           | Description of attribute and level              |
|---------------|-----------|-----------|---|
| O_ALWAYS      | OD        | Odour     | chlorine odour always                           |
| O_MONTH       | OD        | Odour     | chlorine odour once a month                     |
| O_WEEK        | OD        | Odour     | chlorine odour once a week                      |
| O_NEVER       | OD        | Odour     | chlorine odour never                            |
| T_ALWAYS      | TS        | Taste     | chlorine taste always                           |
| T_MONTH       | TS        | Taste     | chlorine taste once a month                     |
| T_WEEK        | TS        | Taste     | chlorine taste once a week                      |
| T_NEVER       | TS        | Taste     | chlorine taste never                            |
| NO_TURB       | TR        | Turbidity | no turbidity from fine air bubbles              |
| MILD_TURB     | TR        | Turbidity | mild turbidity from fine air bubbles            |
| MED_TURB      | TR        | Turbidity | medium turbidity from fine air bubbles          |
| EXTR_TURB     | TR        | Turbidity | extreme turbidity from fine air bubbles         |
| STAIN         | ST        | Stain     | presence of calcium carbonate staining in pipes |

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 672 Table 2. Example of choice-set.  
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| Which of the following alternative would you choose? | A                        | B                        | C                        | D                        |
|--|--------------------------|--------------------------|--------------------------|--------------------------|
| Chlorine odour:                                      | Always                   | 1 day per week           | 1 day per month          | None                     |
| Chlorine taste:                                      | Always                   | 1 day per week           | Never                    |                          |
| Turbidity:   | Absent                   | Medium                   | Extreme                  |                          |
| Calcium carbonate staining:                          | No                       | Yes                      | Yes                      |                          |
| Additional WTP in the bill per year                  | 18€                      | 5€                       | 6€                       |                          |
| Choice   | <input type="checkbox"/> | <input type="checkbox"/> | <input type="checkbox"/> | <input type="checkbox"/> |

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 676 Table 3. Preference Space Fixed Model.  
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|            | Women    |                 | Men   |                 | Joint |                 |
|------------|----------|-----------------|-------|-----------------|-------|-----------------|
|            | <i>M</i> | <i>t</i> -value | $\mu$ | <i>t</i> -value | $\mu$ | <i>t</i> -value |
| Odour      | 0.85     | 9.30            | 0.79  | 8.30            | 0.89  | 8.35            |
| Taste      | 0.28     | 2.86            | 0.27  | 2.66            | 0.31  | 2.73            |
| Turbidity  | 0.85     | 8.95            | 0.79  | 8.58            | 1.04  | 10.57           |
| Stain      | -1.90    | 9.04            | -1.63 | 7.87            | -1.90 | 8.12            |
| Cost       | -0.06    | 4.78            | -0.06 | 5.54            | -0.04 | 3.53            |
| Status Quo | -0.06    | 0.29            | 0.32  | 1.94            | 0.48  | 2.97            |



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Table 4. Preference Space      Summary of model statistics.

| Model              | Number of<br>Parameters | Log<br>Likelihood | BIC  | AIC  | AIC3 |
|--------------------|-------------------------|-------------------|------|------|------|
| Fixed Coefficient  | 18                      | -1343.42          | 2778 | 2723 | 2741 |
| Random Coefficient | 30                      | -1267.18          | 2687 | 2594 | 2624 |
| Influence (Full)   | 38                      | -1200.36          | 2594 | 2477 | 2515 |
| Influence (S)      | 34                      | -1200.36          | 2573 | 2469 | 2503 |

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Table 5. Preference Space Random Coefficient Model.

| Means       | Women    |         | Men      |         | Joint    |         |
|-------------|----------|---------|----------|---------|----------|---------|
|             | $\mu$    | t-value | $\mu$    | t-value | $\mu$    | t-value |
| Odour       | 1.01     | 7.93    | 0.98     | 7.26    | 1.02     | 8.18    |
| Taste       | 0.30     | 2.38    | 0.30     | 2.24    | 0.34     | 2.29    |
| Turbidity   | 1.00     | 7.31    | 1.04     | 7.20    | 1.19     | 9.24    |
| Stain       | -3.69    | 6.00    | -3.04    | 5.71    | -3.14    | 2.60    |
| Cost        | -0.05    | 3.15    | -0.07    | 5.41    | -0.04    | 3.55    |
| Status Quo  | 0.10     | 0.39    | 0.43     | 2.23    | 0.52     | 2.83    |
| Dispersions | $\sigma$ | t-value | $\sigma$ | t-value | $\sigma$ | t-value |
|             |          |         |          |         |          |         |
| Odour       | 0.42     | 2.84    | 0.64     | 3.02    | 0.00     | 0.00    |
| Taste       | 0.44     | 2.22    | 0.48     | 2.69    | 0.66     | 3.90    |
| Turbidity   | 0.58     | 4.27    | 0.71     | 4.46    | 0.46     | 2.82    |
| Stain       | 2.48     | 2.19    | 1.88     | 4.84    | 1.94     | 1.72    |

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Table 6. Preference Space      Result goodness-of-fit for the Influence Model (Full).

| Attribute | R Square |
|-----------|----------|
|           | %        |
| Odour     | 100      |
| Taste     | 100      |
| Turbidity | 100      |
| Stain     | 100      |

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693 Table 7 Preference Space Result estimates of the regression coefficient,  $a$ , for the Influence  
694 Model (S).  
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| Attribute | Women      | Men   |                    |
|-----------|------------|-------|--------------------|
|           | $a^w$      | $a^m$ | $ t\text{-value} $ |
| Odour     | fixed to 1 | 1.34  | 1.89               |
| Taste     | fixed to 1 | 0.47  | 1.69               |
| Turbidity | fixed to 1 | 0.81  | 2.43               |
| Stain     | fixed to 1 | 0.42  | 2.34               |

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698 Table 8 Preference Space The reduced form of the Influence Model (S).  
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| Means       | Women    |                    | Men      |                    | Joint    |                    |
|-------------|----------|--------------------|----------|--------------------|----------|--------------------|
|             | $\mu$    | $ t\text{-value} $ | $\mu$    | $ t\text{-value} $ | $\mu$    | $ t\text{-value} $ |
| Odour       | 1.07     | 8.22               | 0.94     | 6.64               | 1.23     | 7.59               |
| Taste       | 0.26     | 2.08               | 0.25     | 1.95               | 0.39     | 2.39               |
| Turbidity   | 1.07     | 7.68               | 0.97     | 7.36               | 1.48     | 8.91               |
| Stain       | -4.70    | 5.24               | -3.39    | 5.35               | -5.23    | 4.85               |
| Cost        | -0.05    | 3.35               | -0.07    | 5.29               | -0.04    | 3.68               |
| Status Quo  | 0.15     | 0.59               | 0.45     | 2.37               | 0.63     | 3.29               |
| Dispersions | $\sigma$ | $ t\text{-value} $ | $\sigma$ | $ t\text{-value} $ | $\sigma$ | $ t\text{-value} $ |
|             |          |                    |          |                    |          |                    |
| Odour       | 0.52     | 4.45               | 0.75     | 5.20               | 0.37     | 2.72               |
| Taste       | 0.50     | 3.70               | 0.43     | 2.47               | 0.65     | 4.46               |
| Turbidity   | 0.63     | 5.06               | 0.64     | 4.13               | 0.61     | 4.26               |
| Stain       | 3.08     | 5.28               | 2.04     | 4.01               | 2.83     | 3.67               |

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701 Table 9. Preference Space Summary of constrained model statistics.  
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| Model                | Number of Parameters | Log Likelihood | BIC  | AIC  | AIC3 |
|----------------------|----------------------|----------------|------|------|------|
| Women Influence Only | 30                   | -1214.52       | 2581 | 2489 | 2519 |
| Men Influence Only   | 30                   | -1227.23       | 2607 | 2514 | 2544 |

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704 Table 10. WTP Space Summary of model statistics, (cf Table 4).  
705

| Model         | Number of Parameters | Log Likelihood | BIC  | AIC  | AIC3 |
|---------------|----------------------|----------------|------|------|------|
| Influence (S) | 39                   | -1095.13       | 2388 | 2268 | 2307 |

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Table 11. WTP Space Estimates of the regression coefficient,  $a$ , for the Influence Model (S) , (cf Table 7).

| Attribute | Women    |                    | Men   |                    |
|-----------|----------|--------------------|-------|--------------------|
|           | $a^w$    | $ t\text{-value} $ | $a^m$ | $ t\text{-value} $ |
| Odour     | fix to 1 |                    | 1.55  | 1.88               |
| Taste     | fix to 1 |                    | 0.24  | 0.57               |
| Turbidity | fix to 1 |                    | 1.05  | 1.68               |
| Stain     | fix to 1 |                    | 0.75  | 1.73               |
| Lambda    | 0.61     | 4.51               | 0.37  | 3.39               |

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Table 12. WTP Space Result estimates of the normal distribution parameters for  $\ln(\lambda)$  in the Influence Model (S).

| $\ln(\lambda)$ | Women    |                    | Men      |                    | $\delta$ Joint |                    | Total Joint |
|----------------|----------|--------------------|----------|--------------------|----------------|--------------------|-------------|
|                | Estimate | $ t\text{-value} $ | Estimate | $ t\text{-value} $ | Estimate       | $ t\text{-value} $ |             |
| $\mu$          | -2.76    | 5.45               | -2.01    | 6.29               | -0.76          | 0.89               | -3.20       |
| $\sigma$       | 1.70     | 6.14               | 1.92     | 5.60               | 0.20           | 0.99               | 1.28        |

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719 Table 13. WTP Space    Result estimates of the other parameters for the Influence Model (S), (cf

720 Table 8).

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| Means       | Women       |         | Men         |         | Joint       |         |
|-------------|-------------|---------|-------------|---------|-------------|---------|
|             | $\mu$       | t-value | $\mu$       | t-value | $\mu$       | t-value |
| Odour       | 28.81       | 2.10    | 19.92       | 6.10    | 59.36       | 2.00    |
| Taste       | 4.31        | 1.24    | 4.38        | 2.30    | 10.62       | 1.02    |
| Turbidity   | 29.60       | 2.56    | 22.31       | 6.44    | 67.03       | 1.89    |
| Stain       | -155.28     | 1.80    | -112.36     | 4.54    | -279.13     | 1.43    |
| Cost        | fixed to -1 |         | fixed to -1 |         | fixed to -1 |         |
| Status Quo  | 18.13       | 1.27    | 12.09       | 2.99    | 50.76       | 1.48    |
| Dispersions | $\sigma$    | t-value | $\sigma$    | t-value | $\sigma$    | t-value |
|             |             |         |             |         |             |         |
| Odour       | 10.58       | 2.37    | 16.49       | 4.67    | 17.15       | 1.55    |
| Taste       | 10.78       | 2.43    | 6.12        | 4.61    | 19.43       | 1.71    |
| Turbidity   | 13.68       | 2.14    | 12.59       | 7.09    | 22.16       | 1.36    |
| Stain       | 101.68      | 1.69    | 55.93       | 4.25    | 115.25      | 1.70    |

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**Figure 1** Probability density function for  $\lambda$

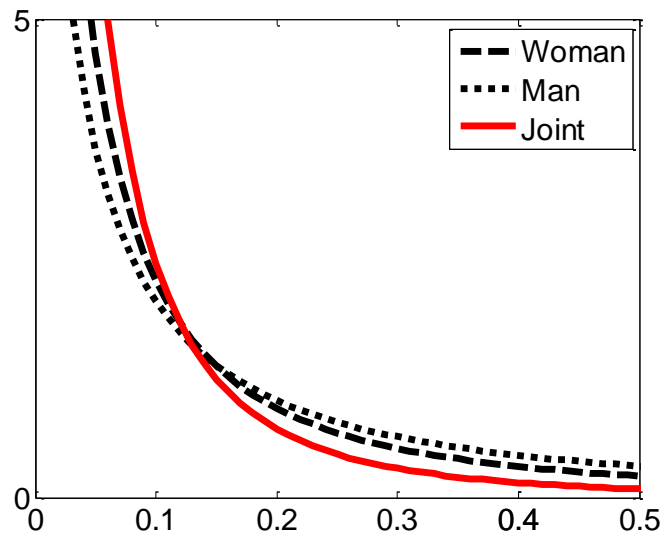


Table 14. WTP Space Distributions of pooled willingness to pay (the product of  $\lambda$  and the various forms of  $\beta$ ).

|           | First Quartile |        |        | Median |        |       | Third Quartile |       |       |
|-----------|----------------|--------|--------|--------|--------|-------|----------------|-------|-------|
|           | Women          | Men    | Joint  | Women  | Men    | Joint | Women          | Men   | Joint |
| Odour     | 0.51           | 0.29   | 0.74   | 1.67   | 1.78   | 2.08  | 5.45           | 8.24  | 5.48  |
| Taste     | -0.09          | 0.00   | -0.06  | 0.12   | 0.29   | 0.26  | 0.86           | 1.78  | 1.12  |
| Turbidity | 0.47           | 0.56   | 0.90   | 1.63   | 2.43   | 2.41  | 5.49           | 9.90  | 6.20  |
| Stain     | -27.97         | -50.43 | -25.85 | -7.67  | -12.79 | -9.93 | -1.84          | -3.10 | -3.59 |

Table 15 WTP Space Pooled willingness to pay correlations - women and men with joint.

|           | Women | Men  |
|-----------|-------|------|
| Odour     | 0.56  | 0.27 |
| Taste     | 0.61  | 0.10 |
| Turbidity | 0.59  | 0.25 |
| Stain     | 0.52  | 0.24 |